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Research Article

# Inclusion of speed and weather measures in safety performance functions for rural roadways

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ABSTRACT

The research on relationships among vehicle operating speed, roadway design elements, weather, and traffic volume on crash outcomes will greatly benefit the road safety profession in general. If these relationships are well understood and characterized, existing techniques and countermeasures for reducing crash frequencies and crash severities could potentially improve, and the opportunity for new methodologies addressing and anticipating crash occurrence would naturally ensue. This study examines the prevailing operating speeds on a large scale and determines how traffic speeds and different speed measures interact with roadway characteristics and weather condition to influence the likelihood of crashes. This study used three datasets from Washington and Ohio: 1) Highway Safety Information System (HSIS), 2) the National Performance Management Research Dataset (NPMRDS), and 3) National Oceanic and Atmospheric Administration (NOAA) weather data. State-based conflated databases were developed using the linear conflation of HSIS and NPMRDS. The results show that certain speed measures were found to be beneficial in quantifying safety risk. Annual-level crash prediction models show that increased variability in hourly operating speed within a day and an increase in monthly operating speeds within a year are both associated with a higher number of crashes. Safety practitioners can benefit from the current study in addressing the issue of speed and weather in crash outcomes.



## 1. Introduction

Current crash prediction methods—such as those in the Highway Safety Manual (HSM)—consist of safety performance functions (SPF) and crash modification factors (CMF) [1]. SPF indicates an equation that can be used to predict crashes as a function of different exposures and CMF indicates a multiplicative factor which is calculated based the proportion of crashes that would be expected after implementing a traffic safety countermeasure. Both SPF and CMF use annual average daily traffic (AADT) data along with geometric and operational characteristics to predict the annual average crash frequency of roadway sites. One of the most significant limitations of the HSM—and quantitative safety performance research in general—is the omission of speed-related factors from nearly all aspects of safety predictive methods. As the second edition of HSM (HSM2) is set to be published in 2023, recent research has made little substantive progress in incorporating speed-related factors into crash predictive models. It is generally anticipated that a vehicle's operating speed during crash impact affects injury severity of crash victims and that speed differential between drivers affects the potential of the frequency of crashes. However, beyond these general relationships, there is minimal consistent evidence for speeds (i.e., posted, average operating, or other) affecting annual crash frequency, although intuitively speed clearly plays a major role in safety. Another key issue is missing is the inclusion of weather data in the development of SPFs. There is an urgent need for research to explore new data and better understand how to effectively quantify highway safety on a daily, hourly, or another short-term basis to overcome these limitations of current methods.

This study collected data from three sources for Ohio and Washington: 1) Highway Safety Information System (HSIS), 2) the National Performance Management Research Dataset (NPMRDS) Version 1, and 3) National Oceanic and Atmospheric Administration (NOAA) weather data to mitigate the current research gap. As these databases are accessible to the state Department of Transportation (DOT) engineers and safety professionals, there is a need for reproducible and transferable modeling techniques, suitable for the state agencies, to improve state specific SPFs for rural two-lane and rural multilane roadways. This project, as part of the U.S. Department of Transportation (USDOT) Safety Data Initiative (SDI) pilot projects, conflated these databases to develop an improved database for the state agencies. This paper was prepared from the final report developed for the rural speed safety

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project [1]. This paper focuses on the SPFs for total (K - fatal, A - incapacitating injury, B - non-incapacitating injury, C – minor injury, and O – property damage only) crashes, fatal and injury (KABC) crashes, and non-injury (PDO) crashes, for Washington and Ohio separately as well as for both states together, for rural two-lane and rural multilane roadways.

## 2. Literature review

The literature review is divided into two sub-sections: 1) studies on operating speed and crash outcomes, and 2) studies on weather and crash outcomes.

### 2.1. Studies on operating speed and crashes

Although speed is considered a major contributing factor of roadway crashes, research findings are inconsistent. While some studies have found that higher speeds are associated with an increased likelihood of collisions, other studies have found the opposite, stating that higher speeds are associated with a lower probability of collisions. A few studies have established statistical models between operating speed and crash occurrence. Findings from the most relevant studies are summarized in Table 1.

Elvik [2] performed a meta-analysis using 98 studies containing 460 estimates of the association between changes in speed and changes in crash frequencies. This study also provides details on power model, which was proposed by Nilsson [3]. The meta-analysis shows that speed changes has a strong relationship to crash frequency change or severity of injuries. Abdel-Aty and Radwan [4] studied speed by capturing the magnitude of speeding relative to the posted speed limit. This speeding indicator variable was shown to affect the crash involvement of male and young drivers. The preliminary analysis of a study conducted by Taylor et al. [5] based in the United Kingdom revealed that, for the compiled dataset, the average speed was negatively related to crash frequency. The authors attributed this finding to the difference in road quality at the road segments sampled; therefore, they created homogenous groups through which the effects of road quality on the relationship between collisions and speed could be captured. The findings show that in a given set of road and traffic conditions the frequency of crashes increases with the speed of traffic, and the higher the speed the more rapidly does crash frequency rise with increases in speed.

Pei et al. [6] showed that crash risk decreases as speed increases. This study also revealed that there might be other explanatory factors, such as road design, weather conditions, and temporal distribution on the relationship between speed and crash risk. Yu et al. [7] employed a Bayesian inference method to model crashes using one year's worth of crash data on I-70 in Colorado. Their model included real-time weather, traffic, and road geometry variables and indicated that the weather condition variables play a significant role in the crash occurrence. This study also suggested that lower speeds at the crash segment and higher occupancy at the upstream segment 5–10 min before the crash time increases the likelihood of crashes. This could be an indication of congestion. However, lower speed and higher crash risk can both be the results of severe weather conditions in which case the relations between the two would be affected by a confounding variable.

Gargoum and El-Basyouny [8] conducted a study of urban two-lane streets in which they attempted to model the relationship between average speed and crash counts while considering effects from confounding factors. They found that that the standard deviation of operating speed seemed to be negatively related to crash frequencies (i.e., increases in the deviation of speeds from the average were related to decreases in crash frequency, and vice versa); however, this

**Table 1**
Key studies on speed-crash relationships.

| Study | Analysis Level | Roadway/Location | Speed Measures | Operating Speed Data Source | Key Findings on Speed-Crash Relationship |
|---|---|---|---|---|---|
| Elvik [2] | Segment | – | Mean Speed and other speed measures | Meta-analysis | Speed changes has a strong relationship to crash frequency change or severity of injurie |
| Nilsson [3] | Segment | – | – | Power model | Relation exists between speed and crashes. |
| Abdel-Aty and Radwan [4] | Segment | Principal arterial, Florida | Speeding relative to posted speed limits | Crash data | The speed measure (speeding relative to posted speed limits) variable was shown to affect the crash involvement of male and young drivers. |
| Taylor et al. [5] | Segment | Different roadways, UK | Average Speed | Road tubes | Excessive speed indicator is strongly and positively associated with crashes. |
| Pei et al. [6] | Segment | Both urban and rural, Hongkong | Standard deviation of average speed | Annual traffic census (ATC) | Crash risk decreases as speed increases. |
| Yu et al. [7] | Segment | Freeways, Colorado | Speed information prior to crash occurrence | Radars | Negative relationships between speed and crash occurrence. |
| Gargoum and El-Basyouny [8] | Segment | Urban two-lane, Canada | Standard deviation of speed | Speed survey operations | Standard deviation of speed seems to be negatively related to collisions. |
| Imprialou et al. [9] | Traffic operation scenarios | Strategic road network, UK | Grouped average speed prior to crash occurrence | Inductive loop detectors | The results of the condition-based approach show that high speeds trigger crash frequency. The outcome of the segment-based model is the opposite; suggesting that the speed–crash relationship is negative regardless of crash severity. |
| Yu et al. [10] | Segment | Urban expressway, China | Average Speed | Using algorithm | The segment-based crash frequency analysis revealed a negative relationship between the crash and speed. |
| Banihashemi et al. [11] | Segment | Urban Interstate, Washington | Operating and Posted Speed Differential | NPMRDS | Severity of crashes measured by the KABC/Total crashes ratio in increasing by increasing the speed differential. |
| Wang et al. [12] | Segment | 234 one-way road segments from eight arterials in Shanghai | Mean speed | Taxi-based high frequency GPS data. | 1.00% increase in mean speed on urban arterials was associated with a 0.70% increase in total crashes |
| Dutta and Fontaine [13] | Segment | 4 lane rural freeway and 6 lane urban freeway segments in Virginia | Speed variations | Physical sensors; INRIX® | Lower average speed is associated with higher crash frequency. However, increase of standard deviation of average speed increases crash frequencies. |

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relationship was only statistically significant at the 10% significance level ($p$-value = .088). The results of Imprialou et al.'s [9] segment-based study also showed the speed-crash relationship was negative regardless of crash severity.

In a recent study by Yu et al. [10], the impacts of aggregation approaches on relationship analyses were investigated based on the advanced traffic sensing data of urban expressway systems in Shanghai. Crash frequency analyses with segment-based and scenario-based approaches were first conducted, and then crash risk analyses were developed at the individual crash level. The segment-based crash frequency analysis revealed a negative relationship between the two. The findings suggested that during congestion periods (i.e. low and moderate speed conditions), the increase in operating speeds are associated with reduced crash likelihoods. Another recent study conducted by Banihashemi et al. [11] found that the severity of crashes (a ratio of KABC crashes to total crashes) increased as the speed differential increased. Using taxi-based high frequency GPS data, Wang et al. [12] used 234 one-way urban arterial segments from eight arterials in Shanghai to determine average speed and speed variation. A hierarchical Poisson log-normal model with random effects was developed. Results showed that 1% increase in average speed is associated with 0.70% increase in total crashes. Dutta and Fontaine [13] continuous count station data and probe data from 4 lane rural freeway and 6 lane urban freeway segments in Virginia. The results show that, for rural roadways, lower average speed is associated with higher crash frequency and increase of standard deviation of average speed increases crash frequencies.

Based on the differing findings about the relationship between speed (both operating speed and speed variability) and crash risks across the literature, there is an opportunity to further advance this debate.

### *2.2. Studies on weather and crash outcomes*

Weather-related crashes are referred to the crashes which happen in the presence of rain, sleet, snow, wet pavement, fog, snowy/slushy pavement, and/or icy pavement. Weather acts through visibility impairments, precipitation, high winds, and temperature extremes to have an influence on driver capabilities, vehicle performance (i.e., traction, stability, and maneuverability), pavement friction, and roadway infrastructure. These impacts can increase crash risk and severity. Various studies have been conducted on driver behavior and crash during rainfall or snowfall. A brief summary of relevant studies is described below.

Examining free-flow speeds on curved highways in rural New York State presented that drivers did not reduce their speeds sufficiently on curves in the presence of wet-pavement conditions [14]. The researchers concluded that drivers did not recognize that pavement friction is lower on wet pavement compared to the dry pavement. Jackson and Sharif [15] used fatal crash data and geospatial analysis to investigate the temporal and spatial distribution of rain-related fatal crashes in Texas from 1982 to 2011. Study results suggest that rain is a contributor to crashes in few counties but at less than 95% confidence in some of the wetter counties. The authors recommended that these counties should be the focus of further research and detailed analysis to explore underlying crash contributing factors.

Mayora and Pina [16] analyzed ten years of crash data from two-lane rural roads on the Spanish National Road System and estimated a skid threshold. This study collected crash data from over 1085 miles of rural two-lane roadways with skid resistance values. The results showed that pavement friction improvement yielded substantial reductions in wet-pavement crash rates averaging around 68%. The results confirmed the importance of maintaining adequate levels of pavement friction to improve safety. Buddhavarapu et al. [17] attempted to establish a relationship between crash severities on horizontal curves and pavement surface condition indices. This study used two Texas Department of Transportation (TxDOT) maintained databases: (a) Crash Record Information System (CRIS) data and (b) Pavement Management Information System (PMIS) data. The findings show that skid number was poorly correlated with crash injury severity on two-lane horizontal curves and the Distress Index and International Roughness Index (IRI) were found to have a statistically significant effect on crash injury severity. Najafi et al. [18] used New Jersey crash data and pavement condition data to develop regression models to investigate the impact of friction on the rate of wet/dry condition vehicle crashes for various urban facilities. The findings showed that friction is not only associated with the rate of wet-condition vehicle crashes, but it also influences the rate of dry condition vehicle crashes.

The literature review reveals that incorporation of weather and speed data were used separately in many studies. Very few studies considered inclusion of both speed and weather information to understand the association between vehicle operating speed, weather and crash outcomes. The current study can be considered as a starting point for more in-depth future investigations in this area.

## 3. Study approach

For crash data analysis, the task of acquiring all safety-related variables is often unattainable. Key challenges include simplified models are preferred for ease of interpretation and usability, access to quality data of the type and quantity needed for a robust study is expensive, and sufficient analytical expertise for both the analyst and user may not be present. Model development using a few key explanatory variables (for example, segment length and traffic volume) can produce relatively simple parsimonious models. For example, if traffic volumes are not available for many local roadways, a simplified SPF can be developed by using only the segment length as an explanatory variable at the cost of more uncertain associated with crash predictions. Such SPFs developed with only segment length exclude many significant explanatory variables and the model-estimated parameter for segment length will have a high risk of bias. The application of the model predictions will then be fundamentally flawed because changes in the omitted variables cannot be captured and the predicted crash frequencies will be incorrect. For practitioners, the developed model will produce biased estimates and would potentially misguide decision making relative to a fully specified and often more complex model for which key variables are explicitly accounted. This study's goal is to develop models for rural two-lane and rural multilane roadways using a dataset that contains the typical variables of length, AADT, and geometric characteristics by also incorporating operational speed and weather data. One significant impact of this study is that it includes several national databases that are accessible to the state DOT safety engineers and practitioners.

## 4. Data description

### *4.1. Data sources*

The two primary databases conflated to achieve the research goal are: 1) The National Performance Management Research Dataset (NPMRDS) and 2) The Highway Safety Information Systems (HSIS) data. Later, this study assigned the weather station data from the National Oceanic and Atmospheric Administration (NOAA) on the conflated database.

### *4.2. HSIS*

The HSIS data is a multi-state safety database that contains crash, roadway inventory, and traffic volume data for a select group of States. Typical data include the type of crash, type of vehicle, sex and age of occupants, fixed-object struck, crash severity, and weather conditions. Traffic volume data contain annual average daily traffic (AADT) data. Roadway data information on roadway cross-section and the type of roadway includes the number of lanes, lane width, shoulder width

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and type, median width, rural/urban designation, and functional classification.

### 4.3. NPMRDS

Since July 2013, the FHWA has procured NPMRDS to support Freight Performance Measurement (FPM) and Urban Congestion Report programs. The NPMRDS includes probe vehicle-based travel time data (for both passenger and freight vehicles) at 5-min intervals for all National Highway System (NHS) facilities. The first version of the NPMRDS is known as 'Version 1' or 'HERE NPMRDS' (which is used in this study). The recent version is known as 'Version 2' or 'INRIX® NPMRDS,' which provides data from January 1, 2017. The NPMRDS data consists of a static GIS file and a database file. The GIS shapefile containing static roadway information was used to relate the travel time information to each traffic message channel or Traffic Message Channel (TMC) segment. The GIS shapefile was provided for visualizing and geo-referencing the NPMRDS data to different maps. The TMC file contains TMC segment geometry information. A database containing a set of files includes average travel times of passenger, freight, and the two combined for identified roadways geo-referenced to TMC segment IDs.

#### 4.3.1. Speed measures

The speed data on TMC segments are recorded every epoch (5-min bin in the raw data). However, the data are not recorded for every epoch; hence, there is a considerable amount of missing values. To overcome this issue, this study considered averaging the data on a daily or a monthly basis. For example, speed measure such as 'monthly average speed' can be calculated as follows:

$$MonthlyAveageSpeed_{TMC_i} = \frac{1}{n}\sum_{k=1}^{n} Speed_{day_k, epoch_e, TMC_i} \quad (1)$$

Where

*Monthly Average Speed*$_{TMC_i}$ = monthly average speed at segment $i$ over a month

$k$ = the number of days in a given month

$Speed_{day_k,\ epoch_e,\ TMC_i}$ = the NPMRDS speed on day $k$ and epoch $e$ at segment $i$

To minimize the missing value issues, the epochs were summed into 15-min epochs resulting in 96 speed records per day. However, in preliminary evaluations, both the 5-min and 15-min speed data did not provide adequate measures about the relationships among the speed, safety, and operational characteristics of the roadway segment due to the large number of missing values. Therefore, other measures of speed were considered. Since the speed data are autocorrelated, speeds observed at consecutive epochs are not necessarily independent of each other. As the distributions of the operational speeds vary from facility to facility for different spatial and temporal factors, several speed measures (for example, peak-hour 85th percentile speed) were examined for the SPF development for the two facility types. For the model development documented in this paper, the following speed measures were considered:

- Average hourly speed.
- Average hourly speed during non-peak and non-event (one hour before and one hour after of a crash occurrence) periods.
- Standard deviation of hourly operating speeds.
- Standard deviation of monthly operating speeds.
- Differences in the operating speeds during weekday and weekend.

### 4.4. Data conflation

Given the list of the data sources and the purpose of the data analysis, the project team developed conflated datasets by integrating information from different sources. The 2015 NPMRDS Static Files were generally produced on a quarterly basis. There are three different Static Files for 2015: January–June (2014Q3), July–October (2015Q3), and November–December (2015Q4). For example, 2015Q4 has 650 additional TMCs in Washington rural NHS roadway networks. In an exploration of the three Static Files, researchers found that over 95% of the NPMRDS TMCs are the same in the rural areas of the states across the three NPMRDS Static Files.

Fig. 1 shows the data conflation flowchart. Two databases (NPMRDS and HSIS for 2015) were used in this study to develop the conflated database for two focus states (Ohio and Washington. The 2015 annual precipitation data from NOAA weather stations were conflated in the HSIS roadway segments. The HSIS segments with all geometric variable, crashes, and precipitation data were later conflated to the TMCs. Total segment lengths (both directions) of Ohio rural two-lane and rural multilane roadways are 1907 miles and 1621 miles, respectively. Total segment lengths (both directions) of Washington rural two-lane and rural multilane roadways are 3552 miles and 521 miles respectively. Fig. 2 illustrates the total number of KABC and PDO crashes in Ohio and Washington.

Tables 2 and 3 list the descriptive statistics of the key variables. The distributions of the speed measures (by facility type) do not show a significant difference between the states. Percentage of days with precipitation in Washington is higher than Ohio, which is as expected. The AADT of Washington is slightly higher than Ohio.

Variable selection is an important step before model development. The correlation plots (see Figs. 3 and 4) show the positive or negation correlation between the variables. In these plots, blue means positive, and red means negative. The stronger the color, the larger the correlation magnitude. The variables of the rural multilane roadways have higher correlation values than the rural two-lane roadways. The correlation plots shown here are based on raw data and for total crashes only.

## 5. Model development and results

This study developed models for total crashes (KABCO), KABC crashes, and PDO crashes, by considering all major geometric variables, five speed measures, and NOAA values after removing some outliers. This section presents the methodology and results related to the SPFs for rural two-lane and rural multilane highways.

### 5.1. Safety performance functions

Separate models were developed for total (KABCO), KABC, and PDO crash. Experience with the regression-based calibration of SPFs and CMFs using total, KABC, and PDO crash indicates that the calibration coefficients often vary among model types for common variables. Some of this variation is likely due to the fact that geometric elements often have a different effect on KABC crashes than on PDO crashes. Also, it is widely recognized that PDO crash counts vary widely on a regional basis due to significant variation in the reporting threshold. When crash frequency varies systematically from county to county, district to district, and state to state because of formal and informal differences in the reporting threshold, the use of PDO crash data to build PDO crash prediction models may yield inaccurate results about the variable influence. Thus, the models were developed for three severity levels to understand the difference in variable effects. Except for curve length and radius, the interaction between the variables was not considered. As noted by Srinivasan and Bauer [19], interactions are not usually considered during SPF development. The authors mentioned that there is no easy way to identify which interactions are important and how they should be included in a model unless there is some theoretical reason for including certain interactions.

#### 5.1.1. Rural two-lane roadways

Different variable combinations and various model forms were examined to identify the best possible relationship between the number

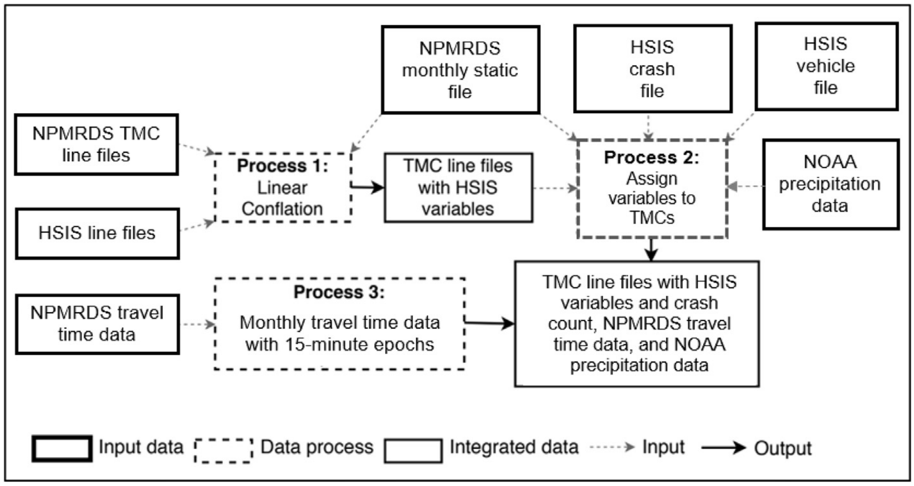


**Fig. 1.** Data conflation.

of crashes and independent variables. The model presented below was informed by findings from several preliminary regression analyses. The following model shows the relation between predicted number of average crash frequencies with segment length, traffic volume, and other variables including different speed measures:

$$N = Len \times e^{b_0 + b_{aadt} \ln(AADT)} \times CMF_{lw} \times CMF_{hc} \times CMF_{sdif} \times CMF_{svar1} \times CMF_{svar2} \times CMF_{sff} \times CMF_{int} \times CMF_{prec} \quad (2)$$

with,

$$CMF_{lw} = e^{b_{lw}(w_l - 12)}$$

$$CMF_{hc} = 1.0 + b_{hc}\left(\frac{L_c}{L}\right)$$

$$CMF_{sdif} = e^{b_{sd}(SpdDiff)}$$

$$CMF_{svar1} = e^{b_{sv1}(I_{svar1})}$$

$$CMF_{svar2} = e^{b_{sv2}(I_{svar2})}$$

$$CMF_{sff} = e^{b_{sff}(SFF)}$$

$$CMF_{int} = e^{b_{int} I_{int}}$$

$$CMF_{prec} = e^{b_{prec}(p_{prec})}$$

where:

$N$ = predicted annual average crash frequency
$Len$ = segment length, miles
$AADT$ = average annual daily traffic, vehicles per day
$CMF_{lw}$ = Lane width CMF
$CMF_{hc}$ = Horizontal curve CMF
$CMF_{sdif}$ = CMF for speed difference between weekend and weekday
$CMF_{svar1}$ = CMF for variance in hourly operating speeds
$CMF_{svar2}$ = CMF for variance in monthly operating speeds

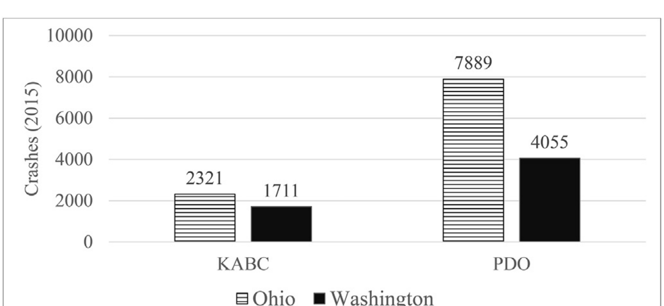


**Fig. 2.** KABC and PDO crashes in Ohio and Washington (2015).

**Table 2**
Descriptive statistics of rural two-lane roadways.

| | Code | Mean | SD | Min | Max |
|---|---|---|---|---|---|
| **Ohio** | | | | | |
| Total Crashes per segment | KABCO | 3 | 4 | 0 | 28 |
| Fatal and Injury Crashes per segment | KABC | 1 | 1 | 0 | 9 |
| PDO Crashes per segment | PDO | 2 | 3 | 0 | 19 |
| Segment Length (mi.) | Len | 3 | 2 | 0.1 | 15 |
| Annual Average Daily Traffic (vehicle per day) | AADT | 5609 | 2581 | 818 | 15,070 |
| Lane Width (ft.) | LW | 25 | 4 | 18 | 48 |
| Presence of Intersection | IntPre | 0.3 | 0.5 | 0 | 1 |
| Percentage of Curve | PerHC | 6.7 | 17.2 | 0 | 100 |
| Percentage of Days with Precipitation | PPrcp | 23 | 45 | 5 | 85 |
| Average Hourly Speed (mph) | SpdAvg | 44.9 | 9.6 | 13.5 | 71.3 |
| Average Hourly Non-Peak Non-Event Speed (mph) | SpdNPNE | 52.1 | 8.3 | 16.9 | 85.0 |
| Standard Dev. of Hourly Operating Speeds (mph) | SDHrSpd | 1.4 | 1.0 | 0.0 | 10.0 |
| Standard Dev. of Monthly Operating Speeds (mph) | SDMonSpd | 0.6 | 0.5 | 0.0 | 7.1 |
| Avg. Spd. Diff. in Weekday/Weekend (mph) | SpdW_W | 1.9 | 0.4 | 1.2 | 5.6 |
| **Washington** | | | | | |
| Total Crashes per segment | KABCO | 4 | 5 | 0 | 34 |
| Fatal and Injury Crashes per segment | KABC | 1 | 2 | 0 | 12 |
| PDO Crashes per segment | PDO | 3 | 3 | 0 | 24 |
| Segment Length (mi.) | Len | 5 | 4 | 0.1 | 25 |
| Annual Average Daily Traffic (vehicle per day) | AADT | 5818 | 4490 | 0 | 26,493 |
| Lane Width (ft.) | LW | 25 | 4 | 20 | 67 |
| Presence of Intersection | IntPre | 0.4 | 0.5 | 0.0 | 1 |
| Percentage of Curve | PerHC | 33.7 | 27.3 | 0.0 | 100 |
| Percentage of Days with Precipitation | PPrcp | 37.1 | 21.9 | 0.0 | 70 |
| Average Hourly Speed (mph) | SpdAvg | 47.3 | 11.2 | 4.5 | 85.0 |
| Average Hourly Non-Peak Non-Event Speed (mph) | SpdNPNE | 55.0 | 10.0 | 6.8 | 85.0 |
| Standard Dev. of Hourly Operating Speeds (mph) | SDHrSpd | 1.7 | 1.6 | 0.0 | 10.0 |
| Standard Dev. of Monthly Operating Speeds (mph) | SDMonSpd | 0.8 | 0.6 | 0.0 | 4.4 |
| Avg. Spd. Diff. in Weekday/Weekend (mph) | SpdW_W | 2.1 | 0.6 | 1.9 | 6.2 |

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**Table 3**
Descriptive statistics of rural multilane roadways.

| | Code | Mean | SD | Min | Max |
|---|---|---|---|---|---|
| **Ohio** | | | | | |
| Total Crashes per segment | KABCO | 4 | 5 | 0 | 36 |
| Fatal and Injury Crashes per segment | KABC | 1 | 2 | 0 | 10 |
| PDO Crashes per segment | PDO | 3 | 4 | 0 | 27 |
| Segment Length (mi.) | Len | 3 | 2 | 0.1 | 12 |
| Annual Average Daily Traffic (vehicle per day) | AADT | 13,216 | 6449 | 3108 | 40,840 |
| Lane Width (ft.) | LW | 48 | 5 | 26 | 69 |
| Presence of Intersection | IntPre | 0.2 | 0.7 | 0 | 1 |
| Percentage of Curve | PerHC | 5.1 | 15.6 | 0 | 100 |
| Percentage of Days with Precipitation | PPrcp | 22 | 16.6 | 5 | 80 |
| Average Hourly Speed (mph) | SpdAvg | 54.3 | 12.1 | 18.6 | 85.0 |
| Average Hourly Non-Peak Non-Event Speed (mph) | SpdNPNE | 59.6 | 9.6 | 26.4 | 86.1 |
| Standard Dev. of Hourly Operating Speeds (mph) | SDHrSpd | 1.2 | 1.4 | 0.0 | 10.0 |
| Standard Dev. of Monthly Operating Speeds (mph) | SDMonSpd | 0.7 | 0.5 | 0.0 | 4.8 |
| Avg. Spd. Diff. in Weekday/Weekend (mph) | SpdW_W | 1.2 | 0.7 | 0.9 | 6.1 |
| **Washington** | | | | | |
| Total Crashes per segment | KABCO | 5 | 6 | 0 | 32 |
| Fatal and Injury Crashes per segment | KABC | 2 | 2 | 0 | 11 |
| PDO Crashes per segment | PDO | 4 | 5 | 0 | 26 |
| Segment Length (mi.) | Len | 4 | 3 | 0.1 | 12 |
| Annual Average Daily Traffic (vehicle per day) | AADT | 17,940 | 12,508 | 0 | 77,827 |
| LaneWidth (ft.) | LW | 48 | 7 | 29 | 76 |
| Presence of Intersection | IntPre | 0.5 | 0.5 | 0 | 1 |
| Percentage of Curve | PerHC | 30.9 | 29.3 | 0 | 100 |
| Percentage of Days with Precipitation | PPrcp | 44.5 | 23.1 | 19.2 | 95.1 |
| Average Hourly Speed (mph) | SpdAvg | 52.0 | 13.3 | 14.5 | 85.0 |
| Average Hourly Non-Peak Non-Event Speed (mph) | SpdNPNE | 57.8 | 11.0 | 20.8 | 85.0 |
| Standard Dev. Of Hourly Operating Speeds (mph) | SDHrSpd | 1.5 | 1.7 | 0.3 | 10.0 |
| Standard Dev. Of Monthly Operating Speeds (mph) | SDMonSpd | 0.8 | 0.8 | 0.0 | 4.7 |
| Avg. Spd. Diff. in Weekday/Weekend (mph) | SpdW_W | 0.8 | 1.3 | 0.0 | 9.2 |

$CMF_{sff}$ = CMF for free-flow speed
$CMF_{int}$ = CMF for presence of an intersection on the segment
$CMF_{prec}$ = CMF for precipitation
$w_l$ = Average lane width in both directions (ft)
$L_c$ = total length of all horizontal curves on the segment
$SpdDiff$ = percent difference of operating speeds between weekend and weekday
$I_{svar1}$ = indicator variable for high variance in hourly operating speeds within a day (= 1 if hourly standard deviation is >1 mph; = 0 otherwise)
$I_{svar2}$ = indicator variable for high variance in monthly operating speeds within a year (= 1 if monthly standard deviation is >1 mph; = 0 otherwise)
$SFF$ = free-flow speed, mph
$I_{int}$ = Indicator variable for intersection presence (=1 if present; =0 otherwise)
$p_{prec}$ = percent of days with precipitation.
$b_j$ = calibrated coefficients ($j$ = hc, sd, svar1, svar2, sff, int, prec).

The inverse dispersion parameter, $K$ (which is the inverse of the overdispersion parameter $\alpha$), is allowed to vary with the segment length. The inverse dispersion parameter is calculated using:

$$K = L \times e^{k} \tag{3}$$

where,

$K$ = inverse dispersion parameter.
$k$ = calibration coefficient for inverse dispersion parameter.

Table 4 lists the model outputs of rural two-lane highways.

The explanations of the model outcomes are described below:

- *Horizontal curves (PerHC):* This variable represents the proportion of the segment with horizontal curves. The two state and Washington models show coefficients positive and significant demonstrating that as the proportion of horizontal curvature increases, the number of crashes increases. In preliminary models, the sharpness of the curve was not found to be statistically significant. This does not mean that the curve sharpness has no effect, but it is possible that the variability in the data variable may be too low to show a statistical significance for this database. Similar reason can be attributed to the insignificance of horizontal curvature variable in Ohio State.
- *Lane width (LW):* This variable represents the average of lane widths in both directions. For both states together, the coefficient is negative for total crashes and KABC crashes, but marginally significant so not reported here. For Washington only data, the variable is significant and negative in all cases. This means that with the increase in lane width on a particular segment, the number of crashes decreases.
- *Operating speed difference (SpdW_W):* This variable represents the percent difference of operating speeds between weekends and weekdays. Generally, this variable is always greater than zero because the operating speeds during the weekend are usually higher than on weekdays unless congestion occurs only during the weekend. The variable value is much greater than zero if the road experiences frequent congestion during the weekday or if the weekend speeds are much higher due to fewer vehicles on this type of roads. The coefficient is significant and positive for both states PDO crashes and for Washington KABCO and PDO crash types. This means, with higher weekend as compared to weekday speeds, more crashes (especially PDO crashes) occur perhaps due to congestion during weekday or higher speeds in the weekends.
- *Standard Deviation in hourly operating speeds (SDHrSpd):* This variable represents the operating speed variation among the hours of a day with an indicator variable of 1 for those segments where the standard deviation was greater than 1 mph. The coefficient is positive and statistically significant for KABC crashes in the two states and Washington only models. A segment with high variation in hourly operating speeds (i.e., >1.4 mph) is expected to experience a higher number of KABC crashes than a segment with a lower variation in hourly speeds.
- *Standard Deviation in monthly operating speeds (SDMonSpd):* This variable represents the operating speed variation among the months of a year with an indicator variable of 1 for those segments where the standard deviation was greater than 1 mph. The coefficient is insignificant for both total and KABC crashes in all models but positive and significant for O crashes in the Ohio only model. A segment with high variation in monthly operating speeds (i.e., >1 mph) is expected to experience a higher number of O crashes than a segment with a lower variation in monthly speeds.
- *Non-peak non-event operating speed (SpdNPNE):* This variable represents the operating speed during non-peak and non-event hours. The coefficient is insignificant for all crashes, irrespective of the data used. This could be due to the low variation in the non-peak non-event speeds between the segments considered in the study.
- *Precipitation (PPrcp):* This variable represents the percent of days with some level of precipitation. The coefficient is negative and significant in most of the models. This finding is counterintuitive because it shows that segments with more precipitation tend to have fewer crashes than other segments. However, it is possible that the vehicle speeds reduce during the wet weather conditions, so may result in fewer crashes. Additional variables are needed to reexamine this finding.
- *Intersection presence (IntPre):* This variable has a value of 1 if at least one intersection is on the segment. The coefficient is positive and

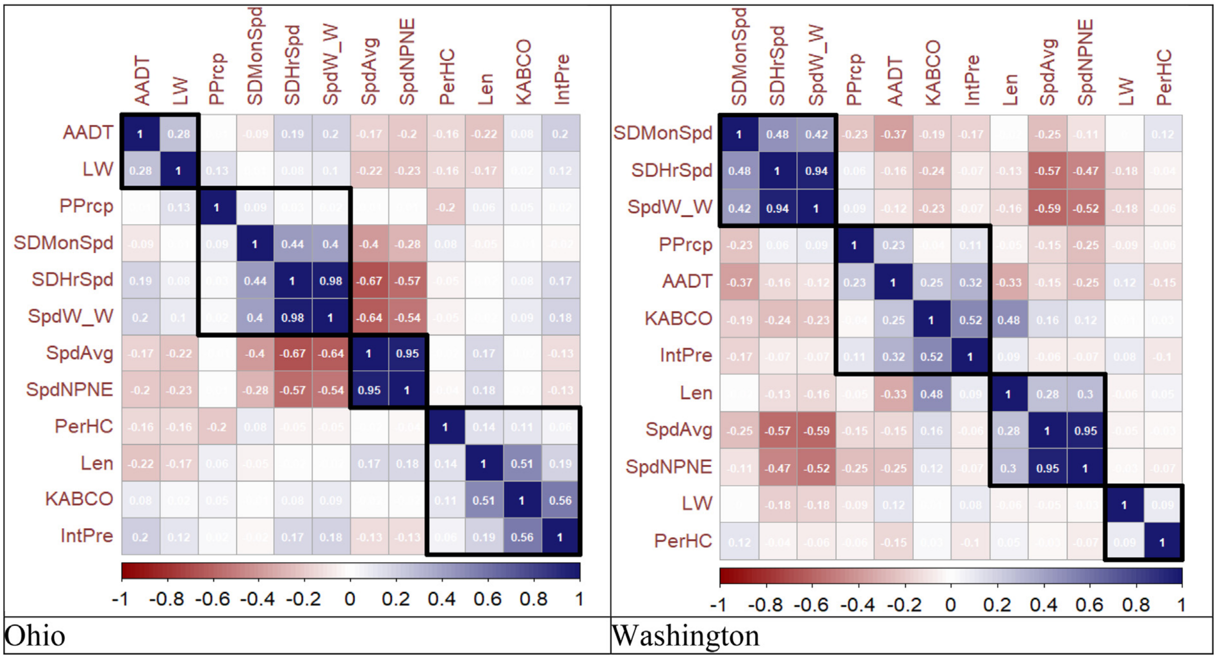


**Fig. 3.** Correlation plots of key variables (Rural two-lane roadways).

significant in all cases. This finding indicates that rural two-lane segments with intersections tend to have more crashes than segments without intersection, as expected. With intersections, the conflict points increase, thus increasing the number of crashes.

- *State effect:* When the two states' data are combined, the coefficient for Ohio is positive and significant. This means that controlling for the other variables, Ohio is expected to experience more crashes than Washington. This finding could be due to differences in weather, terrain, reporting threshold, and other variables that were not considered in the model.

### 5.2. Rural multilane roadways

The form considered for the rural multilane roads was:

$$N = L \times e^{b_0 + b_u + b_{aadt} \ln(AADT)} \times CMF_{lw} \times CMF_{hc} \times CMF_{sdif} \times CMF_{svar1} \times CMF_{svar2} \times CMF_{sff} \times CMF_{int} \times CMF_{prec} \quad (4)$$

where:
$b_u$ = Adjustment for undivided road.

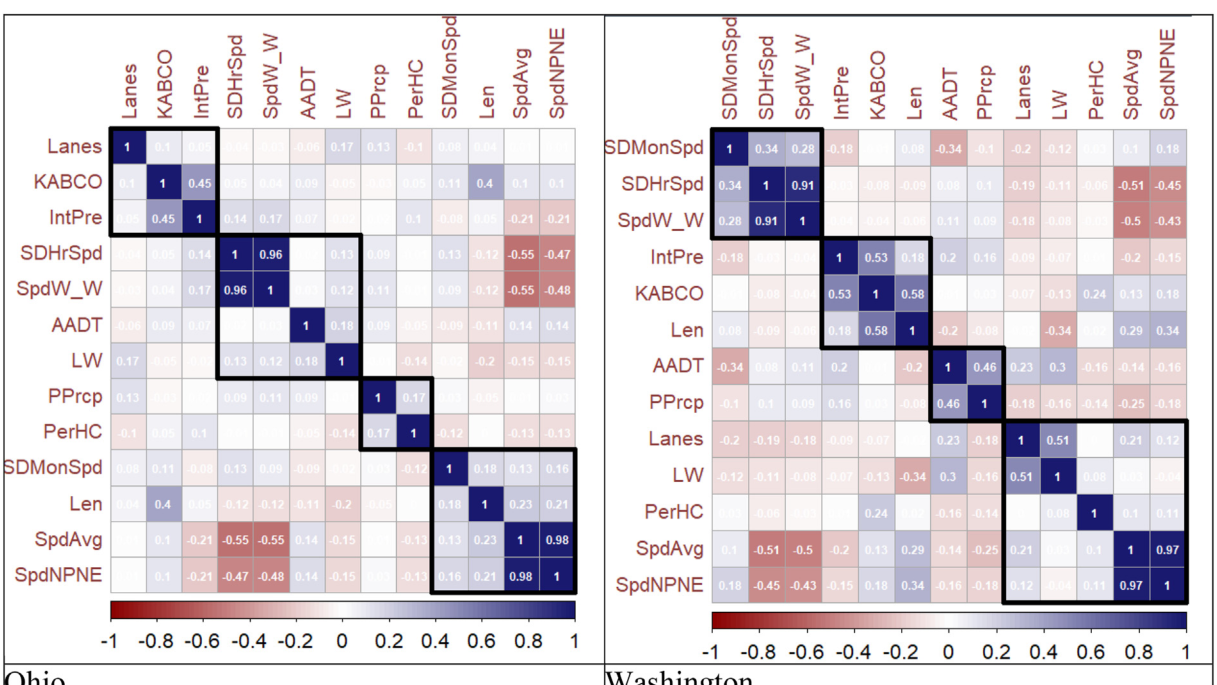


**Fig. 4.** Correlation plots of key variables (Rural multilane roadways).

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**Table 4**
Model estimation results of annual crash frequencies at segments (Rural Two-Lane).

| Variables[a] | Two States | | | Ohio | | | Washington | | |
|---|---|---|---|---|---|---|---|---|---|
| | KABCO | KABC | O | KABCO | KABC | O | KABCO | KABC | O |
| Intercept | −5.8138 | −7.6705 | −5.8097 | −3.6772 | −6.8237 | −3.4111 | −6.5573 | −7.9683 | −6.9051 |
| AADT | 0.6048 | 0.6435 | 0.5679 | 0.3706 | 0.5967 | 0.3352 | 0.6962 | 0.6744 | 0.7048 |
| LW | – | – | – | – | – | – | −0.0962 | −0.1814 | −0.0672 |
| PerHC | 0.8681 | 1.0319 | 0.8230 | – | – | – | 1.1538 | 1.1829 | 1.1356 |
| SpdW_W | – | – | 0.02845 | – | – | – | 0.0444 | – | 0.04454 |
| SDHrSpd | – | 0.1654 | – | – | – | – | – | 0.1878 | – |
| SDMonSpd | – | – | – | – | – | 0.3224 | – | – | – |
| SpdNPNE | – | – | – | – | – | – | – | – | – |
| IntPre | 0.3163 | 0.2769 | 0.3296 | 0.4498 | 0.4074 | 0.3817 | 0.2278 | 0.1801 | 0.2398 |
| PPrcp | −0.5372 | – | −0.6149 | – | – | – | −0.8338 | – | −1.0547 |
| Added effect of Ohio | 0.6332 | 0.4103 | 0.6691 | NA | NA | NA | NA | NA | NA |

Notes: – means not significant at 5% level; NA means not applicable.
[a] Description of variables provided in Table 2.

**Table 5**
Model estimation results of annual crash frequencies at segments (Rural Multilane).

| Variables[a] | Two States | | | Ohio | | | Washington | | |
|---|---|---|---|---|---|---|---|---|---|
| | KABCO | KABC | PDO | KABCO | KABC | O | KABCO | KABC | PDO |
| Undivided road | 0.2686 | 0.3903 | – | 0.4826 | 0.4598 | 0.4513 | – | 0.3376 | – |
| AADT | 0.4848 | 0.3573 | 0.5529 | 0.4335 | 0.3381 | 0.4945 | 0.6473 | 0.6593 | 0.7084 |
| PerHC | 2.0307 | 1.574 | 2.3082 | 1.5865 | – | – | 3.6393 | 0.9047 | 4.7683 |
| SpdW_W | 0.05879 | – | 0.05048 | 0.0666 | – | 0.0599 | – | −0.1504 | – |
| SDHrSpd | – | 0.2418 | – | – | 0.4081 | – | −0.292 | – | – |
| SDMonSpd | 0.3911 | – | 0.4013 | 0.2969 | – | 0.3553 | 0.8381 | 1.0588 | 0.6856 |
| SpdNPNE | 0.0269 | 0.0239 | 0.0251 | 0.0308 | 0.0238 | 0.03055 | – | 0.0598 | – |
| IntPre | 0.5714 | 0.5625 | 0.5797 | 0.6052 | 0.7757 | 0.5664 | 0.452 | −0.0212 | 0.5999 |
| PPrcp | −1.9369 | – | −1.8614 | −1.7573 | – | −2.3932 | – | – | – |
| Added effect of Ohio | 0.8282 | 0.3397 | 1.0050 | NA | NA | NA | NA | NA | NA |
| Inverse dispersion parameter for undivided roads | −0.5868 | −0.2271 | −0.6188 | −0.601 | −0.5042 | −0.5522 | −0.4212 | 0.0506 | −0.417 |
| Inverse dispersion parameter for divided roads | −0.9955 | −0.8616 | −0.9469 | −1.0595 | −0.6138 | −1.0097 | −0.4212 | 0.0506 | −0.417 |
| Intercept | −6.4938 | −6.9752 | −7.4546 | −5.5104 | −6.5777 | −6.0308 | −6.4405 | −11.196 | −7.634 |

Notes: — means not significant at 5% level; NA means not applicable.
[a] Description of variables provided in Table 3.

Table 5 lists the model outputs of rural multilane highways. The explanations of the model outcomes are described below:

- *Undivided road:* This variable represents whether the segment is undivided or divided. The coefficient is positive and significant in almost all cases, except O crashes. This finding indicates that undivided rural multilane roads experience more crashes than divided roads for the same traffic and other conditions. For undivided roads, the likelihood of opposite-direction and turning-related crashes is relatively higher than for divided roads, which may also be a reason why this relationship was not significant for O crashes.
- *Lane Width (LW):* Lane width is not significant for rural multilane models.
- *Horizontal curves (PerHC):* The coefficient is positive and significant in all cases, except for KABC and O crashes in Ohio model. It shows that a higher proportion of horizontal curvature is associated with a higher the number. The sharpness of the curve was not statistically significant in the preliminary models.
- *Operating speed difference (SpdW_W):* The coefficient is significant and positive for KABCO and PDO crashes in the Ohio and two-state models. This means, the increase in the difference in speeds between weekends and weekdays is associated with more crashes perhaps due to occasional congestion during the weekday or higher speeds in weekends.
- *Variance in hourly operating speeds (SDHrSpd):* The coefficient is positive for KABC in Ohio and the two-state models but insignificant for most of the other conditions. The exception is the coefficient for this variable using the Washington KABCO data which was negative indicating a counterintuitive result. Additional investigation into this variable is needed. The positive coefficients for KABC in Ohio and the two-state models show that a segment with variation in hourly operating speeds of more than >1 mph is expected to experience a higher number of crashes than a segment with a lower variation in hourly speeds.
- *Variance in monthly operating speeds (SDMonSpd):* When the coefficient is statistically significant it is positive. A segment with variation in monthly operating speeds of more than >1 mph is expected to experience a higher number of crashes than a segment with a lower variation in monthly speeds.
- *Non-peak non-event operating speed (SpdNPNE):* The coefficient for non-peak non-event times is significant for most of the cases and positive. This finding means that with the increase in non-peak non-event speeds, crashes increase.
- *Precipitation (PPrcp):* The coefficient is negative and significant in most of the models. One possible explanation is that the vehicle speeds reduce during the wet weather conditions, so it may result in fewer crashes. However, extended exploration is needed to reexamine this finding.
- *Intersection presence (IntPre):* The variable is positive and significant in most cases. This finding means that segments with at least one intersection tend to have more crashes than segments without intersection, as expected. With intersections, the conflict points increase, thus increasing the number of crashes.
- *State effect:* When the two states' data are combined, the coefficient for Ohio is positive and significant for O crashes only. This means that controlling for the other variables, Ohio is expected to experience

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the same number of KABC crashes but more O crashes than Washington. This finding could be due to the difference in weather, terrain, reporting threshold, and other variables that were not used in the model.

## 6. Validation and tool development

### 6.1. Model validation

The Cumulative Residual (CURE) plots were used to conduct the validation for models developed using the two states data combined. The CURE plots show the performance of the model with respect to a particular variable. Hauer [20] showed that the model performance is reasonable if the plot of cumulative residuals oscillates around 0, end close to 0, and not exceed the ±2*standard deviation bounds. If the plot of residuals shows any systemic drift, then it can be concluded that the model provides biased estimates. Fig. 5(a–c) show the CURE plots for rural two-lane highway models. All CURE plots show that the model fits the data along with the entire range of AADT values because the cumulative graphs have a random walk oscillating around zero and they ended close to zero. Fig. 5d shows the best-fit CURE plot for rural multilane highway models. The CURE plot for KABC crashes shows that the model fits the data along with the entire range of AADT values because the cumulative graph has a random walk oscillating around zero and it ended close to zero.

### 6.2. Interactive decision support tool

This study developed a prototype interactive decision support tool that incorporated Washington and Ohio data containing the expected total crashes from the final models to show segment-level high-risk analysis [21]. This tool (see Fig. 6) can visually guide the users to explore the segment-based risk analysis. Interested readers can consult Das and White study [22] for additional details on the tool.

## 7. Conclusions

This study examined the prevailing operating speeds and weather data on a large scale and quantified how traffic speed and weather condition interact with roadway characteristics to affect the likelihood of crashes. As both NPMRDS and NOAA data are available to the state agencies, state traffic safety engineers and practitioners can apply the research approach (incorporation of speed and weather information as risk variables in the SPFs) to quantify highway safety risk and anticipate crash occurrence. The current study is a starting point for more in-depth investigation and continued progress in incorporating speed-related factors into crash predictive models. This study has two unique contributions:

- Developed a reproducible approach to conflate different linear networks and incorporate speed and weather measures.
- Quantified the targeted relationship between crashes and influential variables by developing best-fit models that address the impact of operating speed and weather in annual crash predictions.

This study developed SPFs for KABCO crashes, KABC crashes, and PDO crashes, for Washington and Ohio separately as well as for both states together, for rural two-lane and rural multilane roadways within the National Highway System. The findings show that certain speed measures were useful in the development of the annual segment-level statistical models. For example, increased variability in hourly operating speed within a day and monthly operating speeds within a year are both associated with increased crashes (statistically significant) for several of the crash types examined. Majority of the findings of this study are in line with other studies. Few non-intuitive relationships require more investigation. For example, the negative association between precipitation and annual crash frequencies is not intuitive. There is a need for added variables such as surface condition, and visibility measures to re-examine this relationship.

This study is not without limitations. First, this research used roadway segments based on NPMRDS travel time data TMC segment lengths

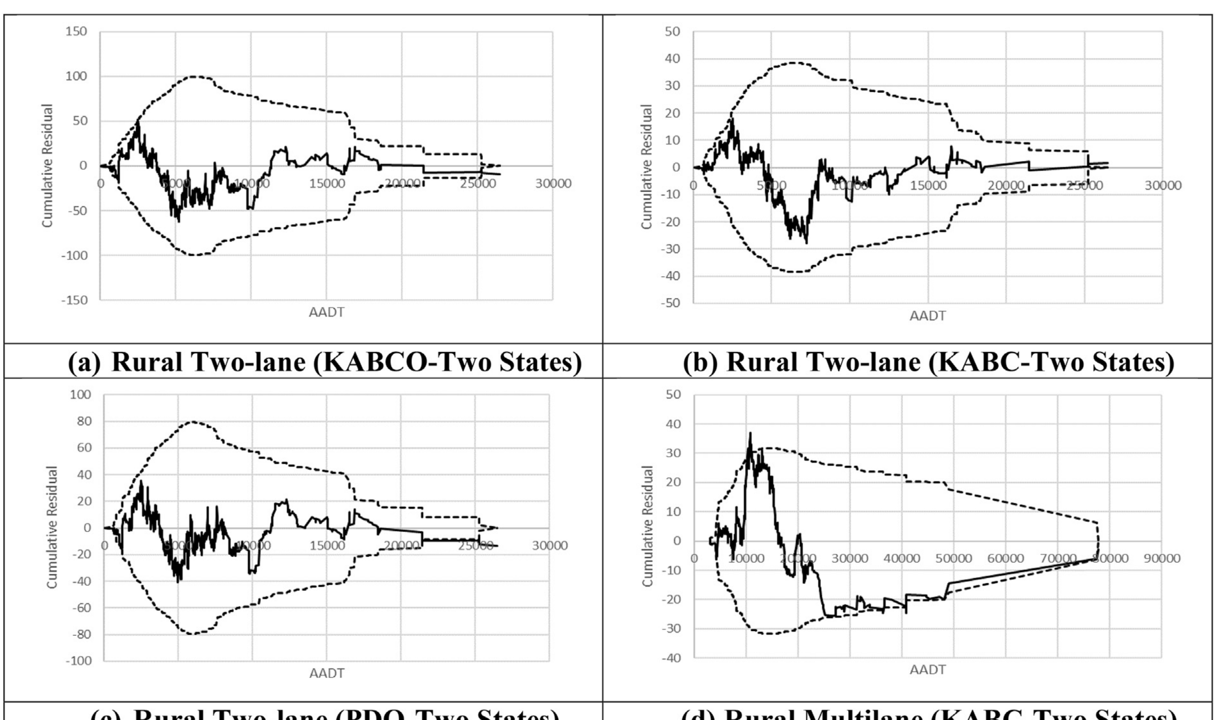


Fig. 5. CURE plots.

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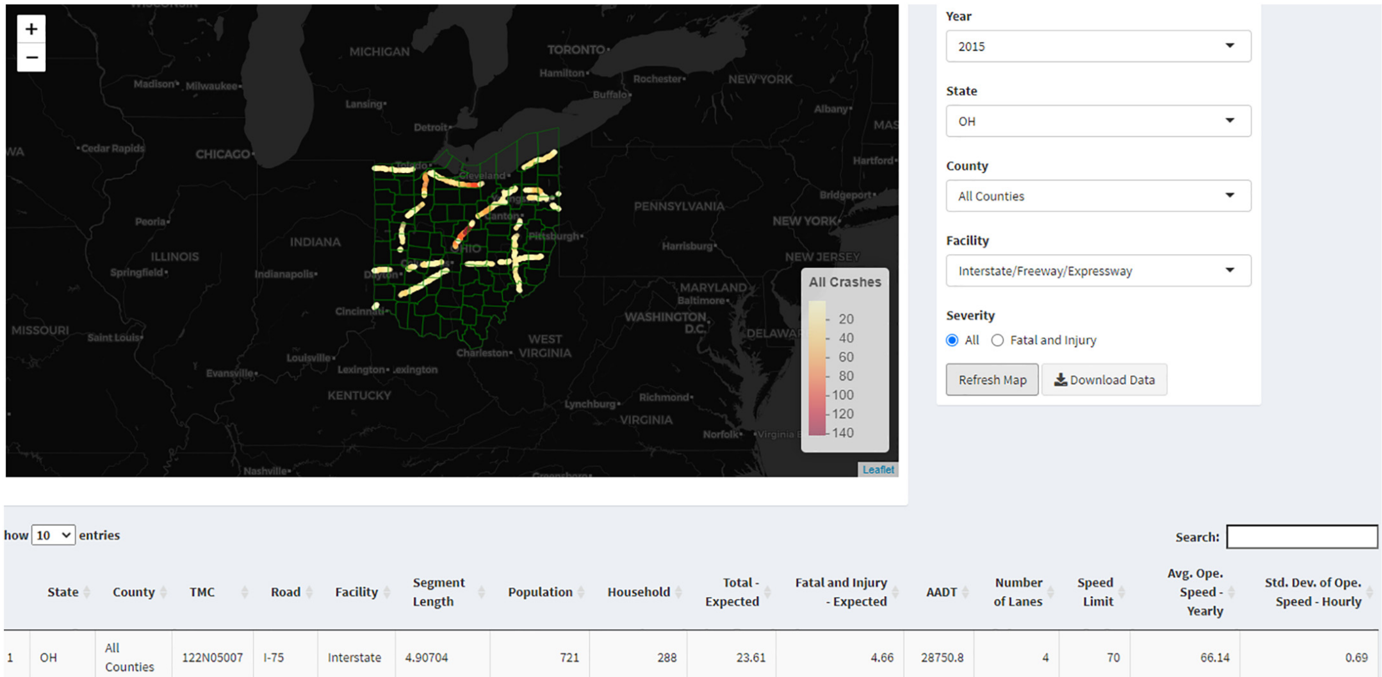


**Fig. 6.** Interactive decision support tool (Source: 21).

(some of the segments are quite long compared to other segments). It is anticipated that uniform resegmentation might be beneficial in improving the model performance. Further examination of the effects of segment length would improve modeling reliability. Second, missing values in the NPMRDS travel time data are higher in lower functional classes. More robust NPMRDS data with fewer missing values would provide more insightful knowledge on how operating speeds affect crashes. Third, many other potential variables (e.g., visibility condition, vertical curve, super elevation) and variable interactions were not performed in this study. Limitation of the current study can be improved in future studies. Subsequent study may examine some limitations found in this study to see if those limitations can be overcome by revised versions of the data, additional data sources, and refinement in modeling.

## Disclaimer

The contents of this paper reflect the views of the authors and not the official views or policies of the OST or the USDOT.

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